Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14695
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Hyperparameter-Tuned Artificial Neural Networks for Early Stunting Prediction in Toddlers

Salnan Ratih Asriningtias [1)*], Citra Dewi Megawati [2)], Dian Kusumaningtyas [3)], Dwi Utari Surya[4)]
[1,2,3,4)] Universitas Brawijaya, Indonesia
[1)]salnan@ub.ac.id, [2)] citramegawati@ub.ac.id, [3)] dian.kusuma@ub.ac.id, [4)]d.utarisurya@ub.ac.id

Submitted :April 14, 2025 | **Accepted** : April 26, 2025 | **Published** : Apr 29, 2025

Abstract: The growing accessibility of varied health data requires the creation of efficient and practical techniques for deriving actionable insights, particularly for the early identification of severe health issues. This study tackles the issue of recognizing stunting—a disorder with enduring health consequences—among children under five by employing Artificial Neural Networks (ANN) with hyperparameter optimization by GridSearchCV. The dataset, sourced from Kaggle, comprises 121,000 records detailing age, gender, height, and nutritional status according to WHO standards. Critical hyperparameters, including dropout rate, batch size, and epochs, were optimized using a five-fold cross-validation approach within GridSearchCV, ensuring a robust model that reduces overfitting and generalizes well to new data. The findings demonstrate a notable performance improvement, as the optimized ANN model attained an accuracy of 99%, exceeding the baseline model's 98%. Enhancements in accuracy, recall, and F1-score across the four stunting classifications—normal, stunted, severely stunted, and tall—underscore the improved specificity and sensitivity of the optimized model. This research demonstrates the efficacy of hyperparameter tuning in ANN for stunting prediction, offering a reliable tool for early intervention in malnutrition management.

Keywords: Artificial Neural Networks, GridSearchCV, Hyperparameter, Optimization, Stunting Prediction

INTRODUCTION

The widespread availability of diverse health data calls for innovative and effective methods to analyze this information, enabling the extraction of critical insights and applying practical solutions to improve health outcomes (Dash et al., 2019). One of the most pressing challenges in medical data analysis is the early detection of developmental and health issues in children, such as stunting—a condition with lifelong impacts if not addressed promptly (Alam et al., 2020). Researchers are actively developing high-accuracy predictive models, decision rules, and optimized input variables to build diagnostic tools for malnutrition-related conditions like stunting. Stunting is a major public health issue marked by hindered growth and developmental delays in children, primarily caused by malnutrition, frequent infections, or insufficient psychosocial stimulation (Putri & Rong, 2021). The World Health Organization (WHO) reports that stunting impacts more than 155 million children under the age of five globally, hindering their physical development, cognitive abilities, and long-term socioeconomic prospects (Nshimyiryo et al., 2019). Early detection of stunting allows for timely interventions, potentially altering a child's life trajectory by mitigating immediate and future adverse effects (Suryawan et al., 2022). However, diagnosing stunting effectively across diverse populations remains challenging, given the complex interplay of factors such as age, sex, height, and nutritional intake that influence growth patterns (Li et al., 2020).

To assist in stunting detection, datasets containing extensive health data on young children, including attributes such as age, height, gender, and nutritional status, are increasingly accessible. However, accurately predicting stunting status based on these variables requires advanced analytical approaches. Traditional statistical methods may be insufficient for capturing intricate, non-linear relationships among multiple variables and outcomes, especially in extensive datasets like this one (Rehman et al., 2022).

Machine learning (ML) and deep learning (DL) approaches, especially Artificial Neural Networks (ANNs), have shown significant potential in tackling comparable diagnostic challenges across different medical fields (Rahman et al., 2021). ANNs, capable of learning complex patterns within large datasets, offer a robust

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14695
e-ISSN : 2541-2019
p-ISSN : 2541-044X

classification framework for stunting prediction by extracting subtle, meaningful features that traditional approaches may overlook (Di Franco & Santurro, 2021). An ANN model is employed to achieve high accuracy in this research, integrating GridSearchCV for hyperparameter tuning to refine model parameters and improve predictive accuracy (Darmiyati et al., 2024). GridSearchCV optimizes key hyperparameters systematically, such as dropout rates, batch sizes, and epoch counts, thereby balancing model complexity and performance through stratified cross-validation (Belete & Huchaiah, 2022).

In previous studies, models have leveraged algorithms such as Support Vector Machines (SVM), Logistic Regression (LR), and ensemble methods to diagnose diseases with reasonable accuracy (Battineni et al., 2020). However, this study proposes a more focused approach by exclusively using an ANN model, optimized with five-fold cross-validation and hyperparameter tuning through GridSearchCV. This method allows for a nuanced exploration of model performance across varied parameter settings, ensuring a model that generalizes well to unseen data and minimizes overfitting risks—a common challenge in machine learning applications involving large datasets.

This research's primary contribution is to advance early stunting detection methodologies by utilizing ANN combined with optimized hyperparameter tuning. This approach aims to achieve near-zero prediction error rates in classifying children under five into appropriate nutritional statuses: severely stunted, stunted, normal, and tall. With such a model, health professionals and policymakers can make more informed, data-driven decisions, improving the allocation of resources and intervention strategies to prevent stunting in high-risk populations.

This paper is organized as follows: Section II reviews prior research on stunting detection and ML approaches, Section III details the dataset, the proposed model's architecture, and analytical approach, and Section IV presents a comprehensive analysis of the results, with comparisons to existing methods. Finally, Section V discusses the implications of these findings for public health policy and potential directions for future research.

LITERATURE REVIEW

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are cognitive instruments modeled after the biological neural networks of humans and animals, capable of effectively learning patterns and forecasting outcomes in high-dimensional spaces (Qamar & Zardari, 2023; Schmidgall et al., 2024).

These networks can associate multiple inputs with corresponding outputs even in complex and noisy datasets. A multilayer perceptron (MLP) represents a simple yet reliable type of feed-forward artificial neural network (ANN). A typical MLP network consists of an input layer, one or more hidden layers, and an output layer (Shariati et al., 2019). The input layer captures incoming values and forwards them to the neurons in the hidden layer. Each neuron calculates a weighted sum of the inputs, adds a bias term, and processes the result using an activation function, as illustrated in Figure 1. The generated output is then transmitted to the neurons in the next layer.

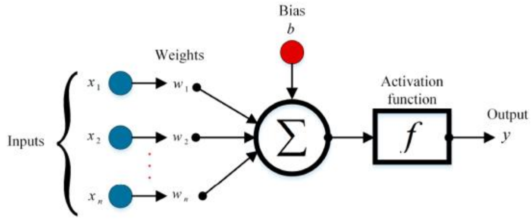

Figure 1. Artificial Neural Network

The mathematical representation of an Artificial Neural Network (ANN) is as following the equation (1)

$$y_j = f\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right) \qquad (1)$$

where x_i and y_j denote the nodal values in the preceding layer i and the subsequent layer j, respectively. n represents the aggregate quantity of nodal values obtained from the preceding layer. w_{ij} and b_j represent the weights and biases of the network, respectively. Activation functions incorporate non-linearity into neural networks, enabling them to recognize and learn intricate patterns (Feng & Lu, 2019). Without an activation function, neurons remain oblivious to value constraints. The activation or transfer function regulates neuron activity by computing weights and applying bias.

This activation function converts input from the range (-∞; +∞) to the range [0; 1]. This function exhibits odd symmetry around the point (0,0,5) and hence satisfies the equation f(-x) = 1 - f(x) (Prabiantissa et al., 2024). Thus, just half of the components suffice to convey the complete function. The mathematical representation of the sigmoid function is provided in Equation (2).

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14695
e-ISSN : 2541-2019
p-ISSN : 2541-044X

$$S(x) = \frac{1}{1+e^{-x}} \quad (2)$$

The sigmoid function is shown in Figure 2.

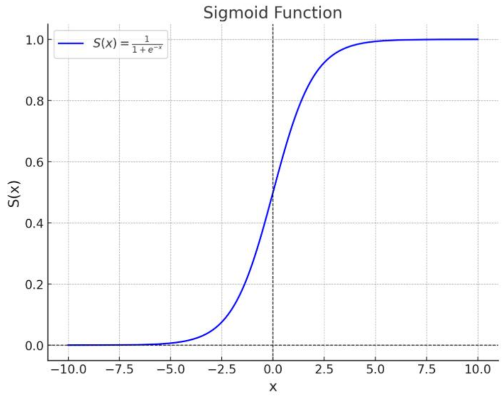

Figure 2. Sigmoid Function

The ReLU (Rectified Linear Unit) function is the maximum of zero and the input valueIt is widely used as an activation function because of its simplicity and effectiveness in hidden layers (Stursa & Dolezel, 2019). The mathematical representation of the ReLU function is provided in Equation (3).

$$f(x) = \max(0, x) \quad (3)$$

The ReLu function is shown in Figure 3.

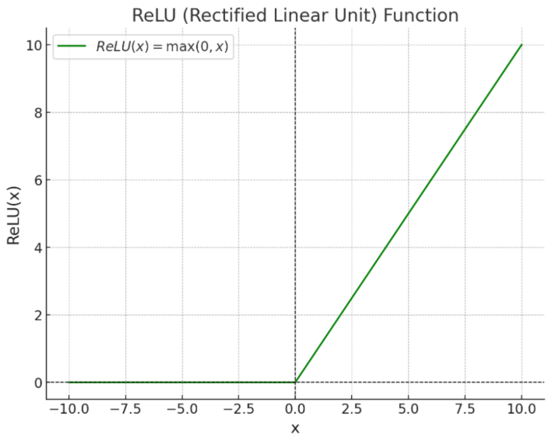

Figure 3. ReLu Function

Gridsearchcv

In most machine learning applications, models are trained using a dataset, and the optimal model is chosen based on specific evaluation metrics. However, this selected model may only be optimal with further tuning. Optimizing hyperparameters is crucial for improving model performance, as it greatly influences both accuracy and generalization ability. This study uses GridSearchCV to identify the optimal hyperparameter values for the Artificial Neural Network (ANN) model applied to stunt detection. GridSearchCV performs an exhaustive search over specified hyperparameter combinations, such as dropout rates, batch sizes, and epoch counts. Cross-validation evaluates each combination to identify settings that yield the highest accuracy and prevent overfitting (Sanil et al., 2023). The hyperparameters-Tuned ANN in this study aim to balance model complexity and training duration, ensuring robust generalization to unseen data. GridSearchCV thus optimizes the ANN model's ability to detect stunting accurately, facilitating a reliable predictive tool for early stunting detection among children under five.

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Performance Matrix

Performance evaluation measures are typically employed in diagnostic decision-making. Evaluation metrics encompass accuracy, sensitivity, specificity, and the F1-score (Juba & Le, 2019). Accuracy quantifies the ratio of correct predictions to the total number of test instances. The calculation for accuracy is outlined in Equations (4), (5), (6), and (7).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1 - Score = \frac{2*(Recall*Precision)}{Recall+Precision} \quad (7)$$

Where TP (True Positive) represents the count of correct predictions within the positive class, while TN (True Negative) indicates the number of correct predictions within the negative class. FP (False Positive) refers to incorrect predictions classified as positive within the negative class, whereas FN (False Negative) denotes incorrect predictions classified as negative within the positive class.

METHOD

Dataset Preparation

The dataset utilized in this study was obtained from Kaggle's "Stunting Toddler Detection" collection, supports early stunting detection in children under five. It includes 121,000 records, each with four key attributes—age (months), gender, height (cm), and nutritional status—based on WHO standards. The dataset categorizes each child's nutritional condition into four classifications: "severely stunted" (< -3 SD), "stunted" (-3 to < -2 SD), "normal" (-2 to +3 SD), and "tall" (> +3 SD). These categories align with standard deviations (SD) of height-for-age, providing a framework for analyzing growth patterns across age and gender. The dataset's completeness (no missing values) enhances its utility for training machine learning and deep learning models, supporting accurate stunting detection (Pradana, 2023). Table 1 describes the dataset.

Table 1. Stunting Detection Dataset Attributes and Information

No.	Feature	Specifics
1	Age (months)	Age of the child in months, ranging from 0 to 60
2	Gender	Male and Female
3	Height (cm)	Height in centimeters, used to assess growth standards based on age
4	Nutritional Status	1 = Severely Stunted (<-3 SD), 2 = Stunted (-3 SD to <-2 SD), 3 = Normal (-2 SD to +3 SD), 4 = Tall (>+3 SD)

Exploratory Data Analysis

This stunting dataset's exploratory data analysis (EDA) provides essential insights into the distribution and relationships of critical attributes, enabling a better understanding of factors associated with stunting (Borges do Nascimento et al., 2021). The dataset comprises 121,000 records of toddlers, with features including age in months, gender, height in centimeters, and nutritional status. As shown in Figure 4, the gender distribution is approximately balanced, consisting of 50.4% female and 49.6% male toddlers. This balance minimizes potential biases in gender-based analysis. Figure 5 depicts the distribution of nutritional status categories—normal, severely stunted, stunted, and tall—across genders, with the majority classified as normal, followed by significant instances of stunting.

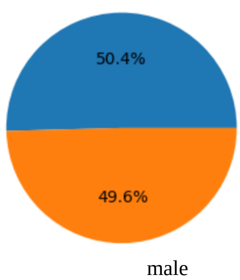

Figure 4. Gender Distribution

*name of corresponding author

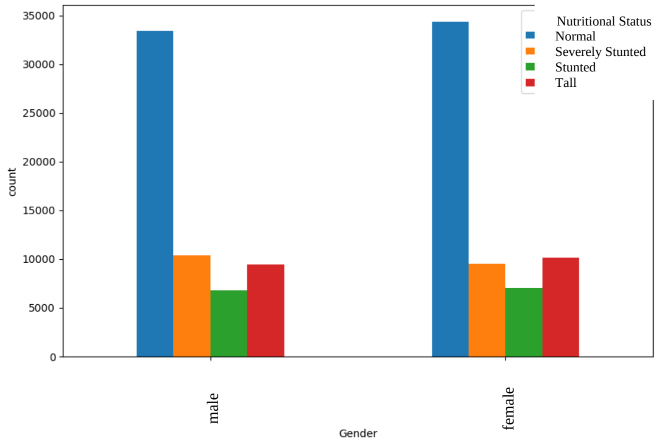

Figure 5. Nutritional Status Distribution by Gender

Figure 6 illustrates the relationship between age and height across these nutritional statuses. Distinct height-for-age trajectories emerge, where the "normal" and "tall" groups align with healthier growth patterns, while "severely stunted" and "stunted" groups show significantly lower height-for-age measurements. These categories are consistent with standard deviations (SD) in height-for-age as per WHO standards, highlighting the dataset's relevance for understanding stunting patterns.

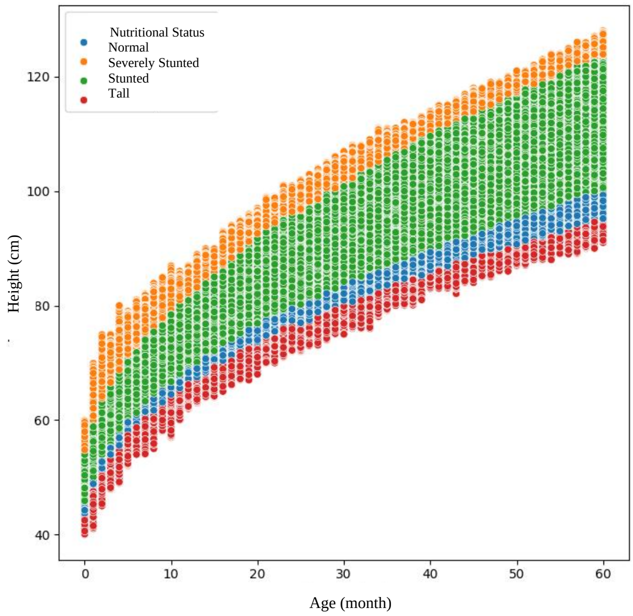

Figure 6. Age vs. Height Distribution Across Nutritional Status Categories

Proposed Method

The workflow of this research, as illustrated in Figure 7, begins with acquiring a dataset focused on detecting stunting toddlers sourced from the Kaggle Repository. This dataset contains key attributes such as age, gender, height, and nutritional status, which are crucial for determining stunting classifications. Before using machine learning models, the dataset is subjected to a preprocessing phase to ready it for analysis. This preprocessing involves encoding categorical variables, particularly converting the gender feature into numerical values, to enable compatibility with machine learning algorithms. Additionally, the dataset is normalized to ensure uniform data distribution across all features, which is crucial for enhancing model accuracy and consistency.

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

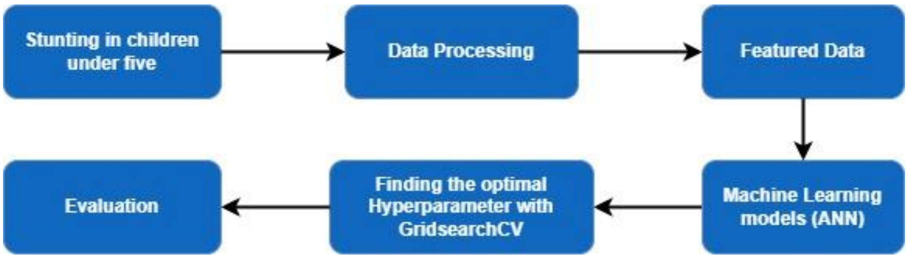

Figure. 7 Methods used in the classification of Hyperparameter-Tuned ANN

After data preprocessing, the refined dataset is utilized to train an Artificial Neural Network (ANN) model, selected for its capability to manage intricate, non-linear relationships in health data. To achieve optimal performance, GridSearchCV is employed to fine-tune the hyperparameters of the ANN model. This method systematically searches for the best combinations of hyperparameters, such as dropout rates, batch sizes, and the number of epochs, by evaluating multiple parameter configurations. This approach ensures that the model balances underfitting and overfitting, thus improving its generalization to unseen data. The model's effectiveness is evaluated through metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive understanding of its ability to classify stunting statuses accurately. Table 2 as its algorithm.

Table 2. Hyperparameter-Tuned ANN Algorithm

	Algorithm
1	**Input**: Dataset X (features) and y (target: Status Gizi).
2	**Load and Preprocess Data**: Load dataset and encode categorical features 80%-20% split feature normalization
3	**Define ANN Model:** Add layers: Dense (128, 64, 32 units) with ReLU and dropout, and output layer with Softmax.
4	**Hyperparameter Tuning with GridSearchCV:** Set up GridSearchCV with parameters: dropout_rate, batch_size, epochs Use StratifiedKFold (5 folds) for cross-validation.
5	**Evaluate Model:** Calculate accuracy and generate classification report
6	**Output**: Optimized ANN model for stunting prediction

RESULT

This research explores the impact of hyperparameter tuning on the predictive performance of an Artificial Neural Network (ANN) model in identifying stunting in toddlers. Hyperparameter optimization was conducted using GridSearchCV, focusing on critical parameters such as dropout rates, batch sizes, and epochs. The dataset was divided into 80% for training and 20% for testing, ensuring a reliable evaluation of the model's performance. To optimize the ANN model, a five-fold cross-validation approach was utilized within GridSearchCV, allowing the model to generalize effectively and avoid overfitting. This study employs the optimum parameters derived using GridSearchCV for each model, as detailed in Table 3.

Table 3. The best hyperparameter of ANN

Model	parameter	GridsearchCV
ANN	Model dropout rate	0,3
	batch size	64
	epochs	100

The Hyperparameter-Tuned ANN model demonstrated a noticeable improvement, achieving an increased overall accuracy of 99%.

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

DISCUSSIONS

Table 4 displays the accuracy, precision, recall, and F1-score for both the baseline ANN model and the Hyperparameter-Tuned ANN models across the four nutritional status classes: normal (0), stunted (1), severely stunted (2), and tall (3). The increase in precision for Class 0 (normal) from 98% in the base ANN model to 99% in the tuned model indicates a reduction in false positives for this category. Precision evaluates the model's capability to correctly identify instances of a specific class while minimizing misclassification of other classes. For Class 2 (severely stunted), the recall improved from 96% in the base ANN model to 97% after tuning, indicating better sensitivity in detecting this critical category. The F1-score for the severely stunted and tall (Class 3) categories also showed a positive shift, reaching 96% and 98%, respectively, thus reflecting the enhanced balance between precision and recall for these classifications.

Table 4. Comparison results

Method	Class	Accuracy	Precision	Recall	F1-Score
ANN	0	98%	98%	**100%**	99%
	1		99%	99%	99%
	2		**96%**	96%	96%
	3		100%	94%	97%
Hypermarameter-Tuned ANN	0	**99%**	**99%**	99%	99%
	1		99%	99%	99%
	2		95%	**97%**	96%
	3		100%	**97%**	**98%**

Through GridSearchCV, we systematically optimized key hyperparameters, including dropout rate, batch size, and number of epochs, to enhance the model's classification capabilities. An 80/20 dataset split was implemented for training and testing, ensuring the model was trained on a comprehensive dataset. The optimal hyperparameters were determined using a five-fold cross-validation within GridSearchCV, providing a reliable approach to generalize the model while minimizing the risk of overfitting. The optimized ANN model attained an overall accuracy of 99%, a notable increase from the baseline model. Improvements in precision, recall, and F1-score across the four stunting categories—normal, stunted, severely stunted, and tall—highlight the enhanced specificity and sensitivity of the Hyperparemeter-Tuned ANN model. For instance, the precision for detecting normal status (Class 0) increased from 98% to 99%, indicating fewer false positives. Furthermore, recall for the severely stunted category (Class 2) rose from 96% to 97%, demonstrating the model's enhanced sensitivity to this crucial classification. These results underscore the effectiveness of GridSearchCV in hyperparameter tuning for ANN, making it a promising approach for stunting detection in toddlers.

CONCLUSION

Using GridSearchCV, key hyperparameters like dropout rate, batch size, and number of epochs were optimized to enhance an ANN model's classification performance. A robust 80/20 training-testing split and five-fold cross-validation ensured reliable generalization and minimized overfitting. The optimized model achieved 99% accuracy, outperforming the baseline model, with notable improvements in precision, recall, and F1-scores across all stunting categories. These results highlight the effectiveness of hyperparameter tuning via GridSearchCV, showcasing its potential for accurate stunting detection in toddlers. In the future, we want to enhance the model for compatibility by investigating additional feature extraction methodologies to enhance accuracy and improve the model's differentiating proficiency.

ACKNOWLEDGMENT(optional)

We gratefully acknowledge the financial support provided through the 2024 UBRICS from Universitas Brawijaya. This funding has been instrumental in enabling the successful execution of our research.

REFERENCES

Alam, M. A., Richard, S. A., Fahim, S. M., Mahfuz, M., Nahar, B., Das, S., Shrestha, B., Koshy, B., Mduma, E., Seidman, J. C., Murray-Kolb, L. E., Caulfield, L. E., & Ahmed, T. (2020). Impact of early-onset persistent

*name of corresponding author

stunting on cognitive development at 5 years of age: Results from a multi-country cohort study. *PLoS ONE*, *15*(1). https://doi.org/10.1371/journal.pone.0227839

Battineni, G., Sagaro, G. G., Chinatalapudi, N., & Amenta, F. (2020). Applications of machine learning predictive models in the chronic disease diagnosis. In *Journal of Personalized Medicine* (Vol. 10, Issue 2). MDPI AG. https://doi.org/10.3390/jpm10020021

Belete, D. M., & Huchaiah, M. D. (2022). Grid search in hyperparameter optimization of machine learning models for prediction of HIV/AIDS test results. *International Journal of Computers and Applications*, *44*(9), 875–886. https://doi.org/10.1080/1206212X.2021.1974663

Borges do Nascimento, I. J., Marcolino, M. S., Abdulazeem, H. M., Weerasekara, I., Azzopardi-Muscat, N., Gonçalves, M. A., & Novillo-Ortiz, D. (2021). Impact of Big Data Analytics on People's Health: Overview of Systematic Reviews and Recommendations for Future Studies. *Journal of Medical Internet Research*, *23*(4), e27275. https://doi.org/10.2196/27275

Darmiyati, I., Soesanti, I., & Nugroho, H. A. (2024). Improving Autism Detection Using GridSearchCV for Severity Level Autism in Indonesian Children. *2024 7th International Conference on Informatics and Computational Sciences (ICICoS)*, 468–473. https://doi.org/10.1109/ICICoS62600.2024.10636869

Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: management, analysis and future prospects. *Journal of Big Data*, *6*(1). https://doi.org/10.1186/s40537-019-0217-0

Di Franco, G., & Santurro, M. (2021). Machine learning, artificial neural networks and social research. *Quality and Quantity*, *55*(3), 1007–1025. https://doi.org/10.1007/s11135-020-01037-y

Feng, J., & Lu, S. (2019). Performance Analysis of Various Activation Functions in Artificial Neural Networks. *Journal of Physics: Conference Series*, *1237*(2). https://doi.org/10.1088/1742-6596/1237/2/022030

Juba, B., & Le, H. S. (2019). *Precision-Recall versus Accuracy and the Role of Large Data Sets*. www.aaai.org

Li, Z., Kim, R., Vollmer, S., & Subramanian, S. V. (2020). Factors Associated with Child Stunting, Wasting, and Underweight in 35 Low- And Middle-Income Countries. *JAMA Network Open*, *3*(4). https://doi.org/10.1001/jamanetworkopen.2020.3386

Nshimyiryo, A., Hedt-Gauthier, B., Mutaganzwa, C., Kirk, C. M., Beck, K., Ndayisaba, A., Mubiligi, J., Kateera, F., & El-Khatib, Z. (2019). Risk factors for stunting among children under five years: A cross-sectional population-based study in Rwanda using the 2015 Demographic and Health Survey. *BMC Public Health*, *19*(1). https://doi.org/10.1186/s12889-019-6504-z

Prabiantissa, C. N., Yamani, L. N., Hakimah, M., Puspitasari, I., & Rozi, N. F. (2024). Implementation of Artificial Neural Network (ANN) to Construct Model for Stunting in Toddlers. *2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, 1–5. https://doi.org/10.1109/AIMS61812.2024.10513149

Pradana, R. P. (2023). *Stunting Toddler (Balita) Detection (121K rows)*. Https://Www.Kaggle.Com/Datasets/Rendiputra/Stunting-Balita-Detection-121k-Rows.

Putri, A. P., & Rong, J.-R. (2021). Parenting functioning in stunting management: A concept analysis. In *Journal of Public Health Research* (Vol. 10).

Rahman, S. M. J., Ahmed, N. A. M. F., Abedin, M. M., Ahammed, B., Ali, M., Rahman, M. J., & Maniruzzaman, M. (2021). Investigate the risk factors of stunting, wasting, and underweight among under-five Bangladeshi children and its prediction based on machine learning approach. *PLoS ONE*, *16*(6 June 2021). https://doi.org/10.1371/journal.pone.0253172

Rehman, A., Naz, S., & Razzak, I. (2022). Leveraging big data analytics in healthcare enhancement: trends, challenges and opportunities. *Multimedia Systems*, *28*(4), 1339–1371. https://doi.org/10.1007/s00530-020-00736-8

Qamar, R., & Zardari, B. (2023). Artificial Neural Networks - An overview. In *Mesopotamian Journal of Computer Science* (pp. 130–139). https://doi.org/10.58496/mjcsc/2023/015

Sanil, G., Prakash, K., Prabhu, S., Nayak, V. C., & Sengupta, S. (2023). 2D-3D Facial Image Analysis for Identification of Facial Features Using Machine Learning Algorithms With Hyper-Parameter Optimization for Forensics Applications. *IEEE Access*, *11*, 82521–82538. https://doi.org/10.1109/ACCESS.2023.3298443

Schmidgall, S., Ziaei, R., Achterberg, J., Kirsch, L., Hajiseyedrazi, S. P., & Eshraghian, J. (2024). Brain-inspired learning in artificial neural networks: A review. *APL Machine Learning*, *2*(2). https://doi.org/10.1063/5.0186054

Shariati, M., Mafipour, M. S., Mehrabi, P., Bahadori, A., Zandi, Y., Salih, M. N. A., Nguyen, H., Dou, J., Song, X., & Poi-Ngian, S. (2019). Application of a hybrid artificial neural network-particle swarm optimization (ANN-PSO) model in behavior prediction of channel shear connectors embedded in normal and high-strength concrete. *Applied Sciences (Switzerland)*, *9*(24). https://doi.org/10.3390/app9245534

Stursa, Dominik., & Dolezel, Petr. (2019). *Comparison of ReLU and linear saturated activation functions in neural network for universal approximation*.

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Suryawan, A., Jalaludin, M. Y., Poh, B. K., Sanusi, R., Tan, V. M. H., Geurts, J. M., & Muhardi, L. (2022). Malnutrition in early life and its neurodevelopmental and cognitive consequences: a scoping review. In *Nutrition Research Reviews* (Vol. 35, Issue 1, pp. 136–149). Cambridge University Press. https://doi.org/10.1017/S0954422421000159

*name of corresponding author